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Implications of future climate change for event-based hydrologic models

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ABSTRACT

Event-based hydrologic models are frequently used for flood design and assessment. These models generally require the specification of loss values that should relate to antecedent conditions in the catchment. The loss values are key calibration parameters, usually defined by matching model output with recorded or derived streamflow information. It is now widely recognized that climate change will impact the hydrologic cycle and affect catchment conditions. Therefore, loss values calibrated using historical observations may not be appropriate for simulating future flooding. We use the method of bottom-up climate change assessment to understand the potential for future performance changes in a calibrated event-based model due to changing antecedent conditions. This is achieved by comparing the results against those of a continuous hydrologic model that accounts for differences in antecedent catchment storages. We find that event-based model performance diverges substantially from the continuous model results under the climate change scenarios, which account for increased dryness and greater extreme rainfall intensities. The results indicate that there is greater uncertainty in event-based model results when simulating drier climatic states, attributed to greater variability in antecedent conditions. However, when simulating increased extreme rainfall intensity (giving rise to larger rainfall events and generally wetter antecedent conditions), the impact of changing antecedent conditions was less important than the models' representations of catchment nonlinearity. This suggests that changing antecedent conditions are not always the key source of potential model performance degradation. Therefore, applying continuous simulation will not necessarily offer an advantage in characterizing future floods. This study highlights the uncertainty facing practicing engineers and hydrologists wanting to account for climate change in flood modelling and design. Large scale changes in engineering practice may be required to ensure that the robustness of flood modelling is maintained in a changing climate.

1. Introduction

Event-based models are commonly used by practicing engineers and hydrologists to simulate historical and design flood events. These models consider a single rainfall event in isolation, as opposed to continuous models that simulate flow over a longer period. While continuous models are more commonly used in research, event-based models are widely applied in flood management around the world and represent traditional practice in most countries (Ball et al., 2016). Recent studies using or developing event-based models have been undertaken in Australia (Charalambous et al., 2013; Gamage et al., 2015), France (Tramblay et al., 2010; Berthet et al., 2009), Italy (Camici et al., 2011), China (Kan et al., 2015; Huang et al., 2016), Iran (Nourali et al., 2016) and Japan (Wang et al., 2007). The application of event-based models for engineering design is recommended by various guidelines including the *USDA National Engineering Handbook Hydrology Chapters: Chapter 17 Flood Routing* (United States Department of Agriculture 2014), *Australian Rainfall and Runoff: A Guide to Flood Estimation* (Ball et al., 2016) and the UK *Flood Estimation Handbook* (Centre for Ecology and Hydrology 1999).

Event-based models are simple to use, but they are limited in their ability to represent the dynamic nature of catchments because they assume simple rainfall loss models that cannot be expected to capture temporal variation in catchment wetness. The moisture stored in a catchment prior to a rainfall event (herein referred to as antecedent conditions) can have a significant impact on the streamflow experienced at the catchment outlet (Hino et al., 1988; Mein and Larson, 1973; Karnieli and Ben-Asher, 1993). Event-based model simulations require the specification of appropriate rainfall loss values to convert total rainfall to excess rainfall while maintaining the intended annual exceedance probability (AEP) for the event (often referred to as AEP-neutral losses). Where streamflow observations are available, it is common practice to calibrate the loss parameters in event-based models. The calibration of loss values allows for deficiencies in the model's process representation to be compensated, so the calibrated values are not necessarily physically representative of the actual rainfall lost to the soil. However, the losses for dry antecedent conditions will still be relatively larger than the losses for wet antecedent conditions (if all else remains equal).

Various hydrologic models used to estimate flood discharges have different approaches to accounting for rainfall losses. In Australia, for catchments where runoff generation is controlled by infiltration excess mechanisms as opposed to saturation excess mechanisms (Johnson et al., 2016), it is common to apply the initial/continuing loss method. This method requires the specification of an initial loss at the start of a rainfall event, followed by a constant loss rate for the remainder of the event. The United States Department of Agriculture Soil Conservation Service (USDA-SCS) curve number method, widely applied in the US, uses information on soil type, land use and antecedent moisture level (dry, medium or wet) to determine rainfall losses (United States Department of Agriculture Soil Conservation Service, 1985). This is one of the

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infiltration methods available in the Storm Water Management Model (SWMM). Other available methods in SWMM include the Green-Ampt Method, which requires specification of the initial moisture deficit in the soil, and Horton's Method, which requires specification of an initial maximum rate of loss (Rossman, 2015). The UK Flood Estimation Handbook recommends calculating initial and maximum soil moisture for design events using two parameters: the base flow index (determined based on soil type) and the proportion of time the catchment was wet between 1961 and 1990 (determined by the UK Met Office through nationwide continuous modelling of soil moisture) (Kjeldsen, 2007). The calculated soil moisture values are then applied in the loss model, which is based on the Probability Distributed Model (Moore, 1985).

Each of these methods inherently assumes that optimized rainfall losses will not be different for future flood events (as opposed to past flood events) because they do not account for systematic changes in antecedent moisture characteristics, herein referred to as nonstationarity in antecedent conditions. We use the definition of Westra et al. (2014) and define the term "nonstationarity" as the tendency of model parameters to vary over time, meaning that their selection is dependent on the calibration period. It follows that models subject to parameter nonstationarity may experience degradation in prediction performance for a climatic scenario that is different from the calibration period.

It is anticipated that future climate change will have a significant impact on the hydrologic cycle (Intergovernmental Panel on Climate Change, 2013). The implication for event-based models is two-fold. Firstly, the rainfall intensities associated with particular AEPs are likely to change (Wasko and Sharma, 2015; Min et al., 2011). This can be taken into account by factoring the design rainfall for a given AEP based on projections for the study area. For example, in Australia and New Zealand rainfall depths are typically scaled up based on future temperature projections relevant to the design life of the project (Ball et al., 2016; Ministry for the Environment 2010).

The second implication of climate change for event-based models is that flood-influencing catchment processes could be impacted (Johnson et al., 2016). Antecedent moisture characteristics in catchments will be impacted by future changes in rainfall and potential evaporation, with trends in soil moisture already being observed (Makra et al., 2005; Destouni and Verrot, 2014) and predicted (Holsten et al., 2009). It follows that loss values calibrated based on historical flood events may not be representative of future losses. If these loss values are applied for climate change assessments or future infrastructure design, flood risk could be estimated incorrectly. In response to this problem, some researchers have suggested moving towards continuous simulation for flood assessment (Johnson et al., 2016) because continuous models can dynamically estimate water storage in a catchment. This gives them the ability to account for the actual conditions in a catchment preceding a particular rainfall event, which has been shown to be important for accurately simulating floods under current conditions (Pathiraja et al., 2012; Wasko et al., 2015). However, at this stage, no direct comparison of the two modelling methods under climate change has been undertaken.

In this study, we use the method of bottom-up climate change assessment (Prudhomme et al., 2010) to examine the implications of potential nonstationarity in rainfall losses for event-based models. Climate change assessments are usually undertaken using a top-down approach, where climate projections derived from General Circulation Models (GCM) are applied in catchment-scale models, generally through bias correction and downscaling procedures. A significant challenge for top-down climate change assessments is the uncertainty surrounding future climate. Assumptions around emissions and the associated response of the environment, as well as implicit simplifications and limitations in climate models, lead to difficulty in discretely defining future climatic regimes for impact assessment (Wilby and Dessai, 2010; Brown and Wilby, 2012). There is reason to believe that current models may not reflect the full range of uncertainty due to issues such as model similarity (Steinschneider et al., 2015). In particular, Mote et al. (2011) noted that no climate model in the Coupled Model Intercomparison Project Phase 3 represented a low-likelihood high-sensitivity response to future emissions.

To overcome these limitations, Prudhomme, Wilby (Prudhomme et al., 2010) introduced bottom-up climate change assessment (also referred to as scenario-neutral climate change assessment), a technique for testing sensitivity to climate change scenarios. They investigated the possibility of climate change increasing flood risk in the UK by more than 20% (the allowance recommended in British design guidelines). The increases in flood risk for a range of feasible climatic changes were modelled to demonstrate how much the climate would need to change to increase flood risk by more than 20%. They related this to available projections to assess the risk that this magnitude of change could occur based on current understanding. Information of this nature is more useful for many decision makers than the results of top-down assessments, which only indicate increases in flood risk for a discrete set of future projections with high uncertainty. Other recent examples of bottom-up climate change assessment include studies by Brown et al. (2012), Culley et al. (2016), Kay et al. (2014) and Poff et al. (2016). We aim to demonstrate that this method of systematically testing the response of a system to increasingly severe climate change scenarios can also be applied to stress-test hydrologic models under change.

By using bottom-up climate change assessment to assess performance divergence between event-based and continuous models under changing climatic conditions, we can understand whether changing antecedent conditions is the most important factor impacting relative model performance (as is commonly assumed (Johnson et al., 2016)). This can provide evidence to fill an existing research gap: whether future flood predictions will be more robust if the current generation of continuous models are adopted in place of commonly-used event-based models calibrated on past observations.

In this study, we evaluate the impact of feasible changes in climate on event-based model performance relative to continuous model results. We apply bottom-up climate change assessment to test the performance divergence between an event-based model and a continuous model under increasingly severe climate change scenarios. We find that, while changing antecedent conditions do have an impact on model performance, there are other model structural differences that also need to be considered when selecting (or developing) a model for climate change assessment.

2. Data

2.1. Observations

The models used in this study were developed based on the catchment draining to the hydrologic reference station *Mitta Mitta at Hinnomunjie* (station number 401203) in Victoria, Australia (herein referred to as the catchment). This catchment falls within a key water-generating area for the Murray Darling Basin (Donohue et al., 2011), an important agricultural region for Australia. Its area is approximately 1546 km^2 (Fig. 1) and its elevation ranges from 545 to 1860 mAHD. The catchment is unregulated with farmland in the lower reaches and forested areas in the upper reaches. The average annual precipitation is approximately 1260 mm over the study period and the average annual runoff is approximately 250 mm.

Daily rainfall data for this catchment was extracted from the Commonwealth Scientific and Industrial Research Organisation's (CSIRO) Australian Water Availability Project daily rainfall grids at 0.05 ° resolution. A weighted average was applied based on grid cell area within the catchment to estimate representative daily rainfall.

The closest pan evaporation station with an adequate length of record is located at Dartmouth Reservoir (station number 082076), about 30 km north of the catchment. This pan has records available from 1975 to present. Daily pan evaporation data was provided by the

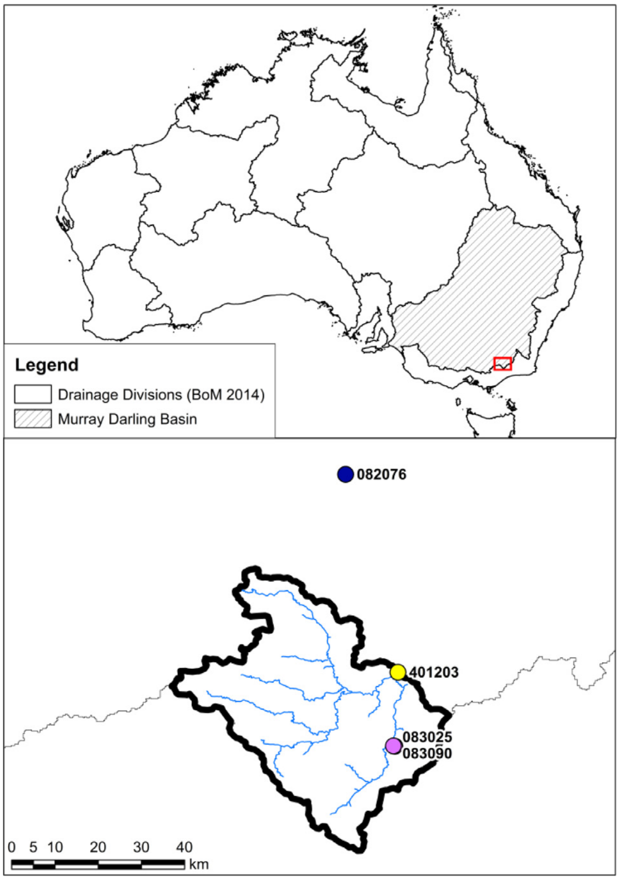

Fig. 1. Catchment location, boundary and identified flowpaths.

Bureau of Meteorology (BoM). Gaps in the pan evaporation series were infilled with monthly averages and a pan coefficient of 0.75 was applied (Doorenbos and Pruitt, 1977).

While temperature data was not required as an input to the hydrologic models, it was used to inform climatic correlations in the climate generator (Section 2.2). Two neighbouring stations (station numbers 083025 and 083090, located about 250 m apart) are situated within the catchment. Daily maximum temperature data was obtained from the Bureau of Meteorology for these two stations. The record for station 083025 begins in 1957 and ends in 2009, while station 83090 has a record beginning in 2004. The datasets during the overlapping period were compared and found to have a high correlation ($r = 0.998$), with only 6% of daily measurements differing by more than 1 °C. Data from 083025 was applied for years preceding 2005, with data from 083090 used to complete the record.

2.2. Climate scenarios

The future climate scenarios used in this assessment were informed by the CSIRO and BoM climate change assessments for Australia (Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology, 2015). Because the catchment is located in Southern Australia, projections from this region were applied. Two of the relevant projections for future rainfall are summarized as:

- A decrease in wet season (winter/spring) rainfall, with reductions of about 18% projected for June through November by 2090 under Representative Concentration Pathway (RCP) 8.5. Some GCMs project reductions greater than 30%.
- An increase in the intensity of extreme rainfall, with 5% annual exceedance probability (AEP) rainfall over one day expected to increase by around 25% by 2090 under RCP 8.5 (with the 90th percentile at 30%).

It is important to note that rainfall projections derived from GCMs are uncertain and vary between studies (Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology, 2015). A key benefit of bottom-up climate change assessment is that a wide range of potential future changes can be included in the investigation and the sensitivity of model performance can be explored to identify any particular weaknesses.

The climate generator described by Srikanthan and Zhou (2003) was used to generate climate data representing future scenarios. This tool uses recorded climate data at a site to calibrate parameters describing the observed sequences and cross-correlations between variables. It then generates new replicates with equivalent climatic statistics and cross-correlations. Maintaining the cross-correlations provides an important advantage because the climatic sequences vary in a consistent, physically realistic way (for example, the potential evaporation will typically be higher on a hot day).

The climate generator considers rainfall as the primary variable. Rainfall time series are stochastically generated using a two-step process. First, a series of wet/dry days is simulated using a first order Markov chain. The probability of a wet day can be expressed as (Siriwardena et al., 2002):

$$\pi = \frac{p_{w|d}}{1 + p_{w|d} - p_{w|w}} \tag{1}$$

Where $p_{w|d}$ is the likelihood of a dry day being followed by a wet day and $p_{w|w}$ is the likelihood of a wet day being followed by another wet day (herein referred to as the wet day persistence). The rainfall depth for a given wet day is sampled from a gamma distribution with the following probability density function (Siriwardena et al., 2002):

$$f(x) = \frac{\left(\frac{x}{\beta}\right)^{\alpha-1} \exp\left(\frac{-x}{\beta}\right)}{\beta\Gamma(\alpha)} \tag{2}$$

Where α is the shape parameter and β is the scale parameter of the gamma distribution Γ. Climate series for additional variables are generated as described in Srikanthan and Zhou (2003).

The generator was modified so that the calibrated parameters describing the historical climatic series could be perturbed, producing future climate replicates that maintain the observed correlations between variables. For this assessment, two parameters were adjusted to represent the range of potential future climatic conditions projected for Southern Australia. The wet day persistence (Eq. (1)) between June and November (herein referred to as the wet season wet day persistence) was decreased in 2% increments to a maximum of 30% below its baseline value. This produced climate sequences that were drier overall in winter and spring without decreasing the likelihood of high intensity rainfall (as would be the case if a decrease in the average rainfall was modelled). This is consistent with projections in Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology (2015).

The distribution of rainfall was adjusted to increase simulated rainfall depths based on the Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology (2015) projections for extreme events. This was achieved by increasing the β parameter (Eq. (2)) in 2% increments to a maximum of 30% above its baseline value.

Simulating the full range of parameter perturbations for each of the two variables in every possible combination gave a total of 256 scenarios. For each scenario, 100 climatic sequences (each 100 years in length) were generated to provide a range of possible climate realisations that represent the specified conditions for that scenario. The chosen length and number of time series aimed to represent the potential climatic variability without becoming computationally burdensome.

The climate generator represented the existing climatic conditions (herein referred to as the current climate scenario) well for most statistics, with a slightly high bias for the annual maximum rainfalls (Fig. 2a).

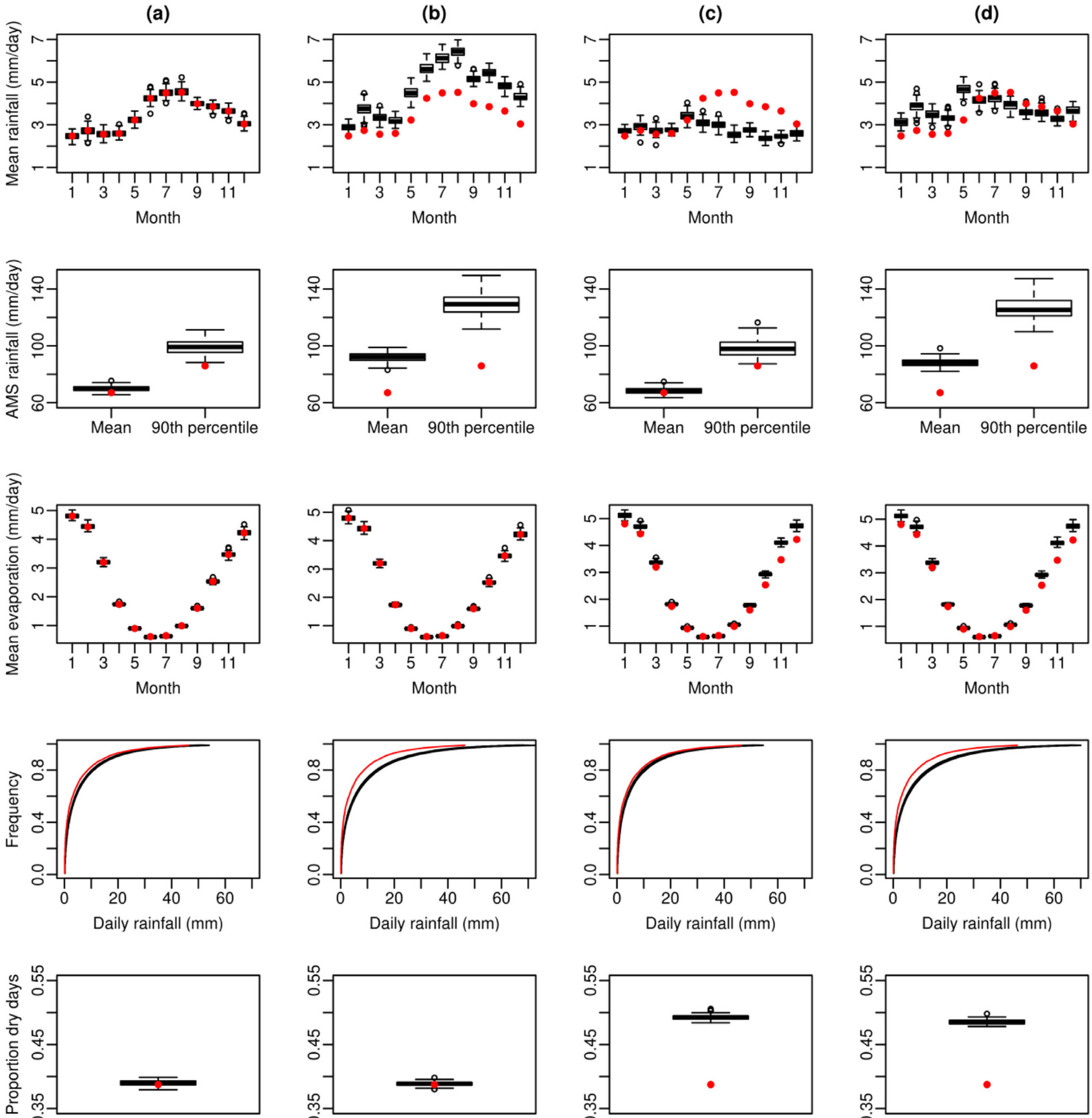

Fig. 2. Observed climate series statistics (red) and statistics of 100 generated sequences (black) for (a) current climate scenario, (b) 30% increase in β parameter, (c) 30% decrease in wet day persistance applied from june to november and (d) 30% increase in β parameter and 30% decrease in wet day persistance applied from june to november. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Adjusting the relevant parameters by 30% (the most extreme cases considered in this study) led to substantial shifts in the climatic sequences. Adjusting the β parameter increased the rainfall distribution of the sequences to favor greater rainfall depths, as well as increasing the overall mean rainfall (Fig. 2b). Adjusting the wet season wet day persistence reduced the average rainfall over the relevant months, as well as increasing the proportion of dry days (Fig. 2c). Because correlations between variables were maintained, adjusting the wet season wet day persistence also impacted the potential evaporation during some months. It had negligible effect on the annual maximum rainfall series. When both parameters were perturbed by 30%, the average rainfall of the generated sequences between June and November was generally slightly less than the historical average rainfall, but greater than the average rainfall when only wet season wet day persistence was perturbed (Fig. 2d).

The two key rainfall statistics for which potential future changes are reported by Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology (2015) – wet season rainfall and 5% AEP rainfall – cannot be directly perturbed in the climate generator, but were altered through perturbations to the wet season wet day persistence and β parameters (Fig. 3). The changes in wet season rainfall and 5% AEP rainfall achieved using the climate generator encompass the range of potential changes projected by Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology (2015). The wet season rainfall is projected to decrease, with some GCMs projecting reductions

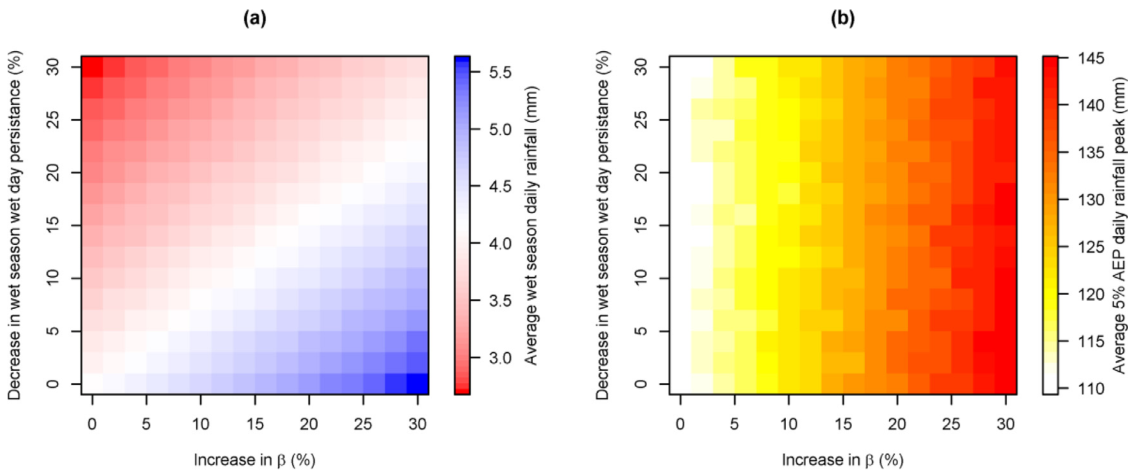

Fig. 3. Average value of (a) wet season daily rainfall and (b) 5% AEP peak daily rainfall over 100 generated sequences for each climate scenario, represented by a single square on the 30 × 30 grid (256 scenarios in total). Historical conditions for each statistic are represented by white. (For interpretation of the colour scale in this figure, the reader is referred to the web version of this article.)

greater than 30% for high emissions scenarios (Commonwealth Scientific and Industrial Research Organisation, Bureau of Meteorology, 2015). Correspondingly, the largest decrease in average wet season daily rainfall produced in the climate sequences is 35% (Fig. 3a – from 4.1 mm to 2.7 mm). The 5% AEP daily rainfall could increase by up to 30% and the maximum increase achieved in the generated sequences is 30% (Fig. 3b – from 111 mm to 145 mm). It can be seen that the 5% AEP rainfall depth is mainly influenced by changes in the β parameter (with some random noise in the results), but the wet season daily rainfall is impacted by both parameters. The overall shift towards drier conditions in winter and increased extreme rainfall is represented to varying degrees in the modelled scenarios.

3. Methodology

We used the approach of bottom-up climate change assessment to understand how much the climate would have to change for the results of an event-based model to diverge significantly from the results of a continuous simulation model. As discussed in Section 2.2, we defined a set of scenarios with increasingly severe changes in climate statistics. We then tested these scenarios in an event-based model and a continuous model and compared the results.

3.1. Model development

3.1.1. Continuous model – GR4J

The continuous model GR4J (Perrin et al., 2003) was adopted to create runoff series that could be used to simulate the possible catchment response to changes in antecedent conditions. A lumped conceptual model was selected over a more detailed distributed model because a large number of simulations were required to represent different future climate scenarios, as well as natural variability within these scenarios.

The GR4J model was calibrated using 39 years of discharge observations from the associated hydrologic reference station (401203), with rainfall and PET observations as inputs (Section 2.1). The Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) was maximized to 0.71 using the Shuffled Complex Evolution (SCE-UA) method (Duan et al., 1992). Since this study focuses on floods, the simulation results were checked against the observations for the largest modelled flow event each year. The modelled flood peaks matched the observations with an average ratio of modelled to observed peak of 1.07 (median 1.06). The flood volumes had an average ratio of modelled to observed volume of 1.11 (median 0.94). The model performance is considered adequate for this study, which focuses on performance divergence between different model types under change, rather than absolute model performance under historical conditions.

A recursive digital filter with a filter parameter of 0.925 was used to estimate the baseflow component of the GR4J results (Nathan and McMahon, 1990; Lyne and Hollick, 1979). This was subtracted to produce surface runoff series, because the event-based model considers surface runoff only. Note that the GR4J results discussed hereafter refer to the results with baseflow removed, rather than the direct GR4J output.

Because continuous models have different methods of accounting for stored moisture, the analysis was also undertaken using the Australian Water Balance Model (Boughton, 2004). The extent of divergence between event-based and continuous model results under climate change was comparable for the two assessments, so only the results obtained using GR4J are presented.

3.1.2. Event-based model – Watershed Boundary Network Model (WBNM)

The event-based model WBNM was used in this assessment because it is commonly used in industry and open source. WBNM employs the initial/continuing loss model, which is common practice in Australia (Ball et al., 2016).

WBNM transforms the excess rainfall hyetograph to a runoff hydrograph for each subcatchment by combining the continuity equation and the storage-discharge relationship to give the following routing equation (Boyd et al., 1996):

$$I(t) - Q(t) = \frac{dS}{dQ}\frac{dQ}{dt} = kmQ^{m-1}\frac{dQ}{dt} \tag{3}$$

Where *I(t)* is the inflow from excess rainfall (m^3/s), *Q(t)* is the outflow (m^3/s), S is the volume stored on the surface (m^3), t is the time (s), k is a scaling parameter and m accounts for the nonlinearity of the subcatchment response. This method of calculating the storage-discharge relationship is similar across common hydrologic models used in Australia. In WBNM, the lag time for each subcatchment is calculated based on the relationship derived by Askew (1970):

$$LAG = cA^{0.57}Q^{-0.23} \tag{4}$$

Where c is the lag parameter and A is the subcatchment area (km^2). Based on this equation, the value for m in Eq. (3) is generally fixed at 0.77 in WBNM. The value for m in common Australian models ranges from 0.6 to 0.8 (Ball et al., 2016). It is worth noting that model structures vary significantly between event-based hydrologic models used in different parts of the world. ReFH (commonly used in the UK) uses the unit hydrograph routing method (Kjeldsen, 2007), which assumes a linear catchment response. SWMM (commonly used in the USA) converts excess rainfall depth into a volumetric flow rate using the Manning

equation, which inherently assumes a higher rate of nonlinearity than WBNM.

The WBNM model for this study was developed based on available information characterizing the catchment (Section 2.1). Subcatchments (63) were delineated in ArcGIS based on SRTM digital elevation data at 1 Arc-second resolution (obtained from https://earthexplorer.usgs.gov/) to provide data on the subcatchment areas, centroid locations and outlet locations. Based on inspection of aerial imagery, the catchment consists of farmland and naturally vegetated areas, so the impervious fraction was set to zero. A standard lag parameter (*c*) of 1.7 was applied. Because the catchment has a large area (1550 km^2) and a time of concentration of approximately five days, a daily timestep was selected. The time of concentration was estimated by applying a constant rainfall rate of 1 mm/day in the WBNM model with no losses and identifying when a constant flow rate was achieved at the catchment outlet.

The assessment was undertaken for the 5% AEP flood event because it is of common interest in engineering design and likely to be adequately represented in the 100 year climate sequences. Each rainfall event was assumed to begin either five days prior to the associated rainfall peak (five days being the estimated time of concentration for the catchment) or on the most recent dry day (zero rainfall).

The WBNM model was calibrated against the continuous model results for the current climate scenario. The Kling-Gupta Efficiency (KGE) (Gupta et al., 2009) averaged over the 100 current climate 5% AEP events was used as the objective function. This was found to better reflect model performance than the NSE for single events because it was able to recognize good model performance in reproducing peaks and volumes, even when the timing was offset. The NSE was found to be overly sensitive to timing (as discussed in Moussa (2010)) and sometimes favoured zero flow results over delayed peaks. The SCE-UA optimization method was applied to maximize the KGE to −0.09. The poor average performance, even when optimized, reflects the high variability in individual simulations when a single set of rainfall losses was applied to 100 different events.

3.2. Model evaluation

For each scenario, we assessed the performance of the event-based model (which was calibrated to the current climate scenario) relative to the continuous model that can dynamically account for changing catchment moisture storages. We defined four performance measures to assess divergence in model results:

- Average ratio of WBNM storm volume to GR4J storm volume
- Median ratio of WBNM storm volume to GR4J storm volume
- Average ratio of WBNM peak flow to GR4J peak flow
- Median ratio of WBNM peak flow to GR4J peak flow

These ratios demonstrate the similarity of the WBNM results to the continuous model results in terms of flood statistics that are of interest in engineering design. Average and median values were calculated over 100 simulated storm events where a single storm event was extracted from each of the climate sequences generated for each scenario. Taking the average/median performance over a number of simulations allowed for the detection of systematic changes in model performance that would be overwhelmed by random noise if single events were used.

3.3. Bottom-up climate change assessment

The bottom-up climate change assessment for this study involved four key stages (Fig. 4). The first stage (Fig. 4, red) involved calibration of the climate generator to observations, followed by generation of current and future climate sequences (Section 2.2).

The second stage (Fig. 4, blue) was continuous model development and application. A GR4J model of the catchment was developed through calibration to discharge observations from the hydrologic reference station 401203 (Section 3.1.1). The generated climatic sequences (for both current and future climate scenarios, 256 scenarios in total with 100 sequences each) were used as the inputs to the calibrated GR4J model and the baseflow was subtracted from the simulated flows. This produced the continuous surface runoff results for each climatic sequence.

The 5% AEP peak runoff was estimated from each time series based on Cunnane's plotting position (Cunnane, 1978). The rainfall and simulated surface runoff from GR4J associated with the 5% AEP flood in each sequence were extracted for simulation in the WBNM model.

The third stage (Fig. 4, green) was calibration and application of the event-based model. The WBNM model was parameterized based on available information about the catchment (Section 3.1.2). The initial and continuing loss values were calibrated based on the continuous model results for 5% AEP events extracted from sequences with unperturbed climatic statistics (current climate). The same losses were then applied to model future climate scenarios.

In the final stage (Fig. 4, purple) the WBNM runoff hydrographs were compared with those of the associated continous simulations to assess the relative model performance (Section 3.2). The changes in relative model performance for increasingly severe climate scenarios were demonstrated using a response surface for each performance measure. These surfaces are commonly used in bottom-up climate change assessment to indicate the sensitivity of a system or process to several hypothetical changes (Prudhomme et al., 2010). The lower left corner of the surface represents a no-change scenario and incremental changes in climatic variables are represented along the respective axes. A colored grid is used to show the impacts of these changes on the system or process of interest (in this case, event-based model performance relative to GR4J results).

The same process was undertaken with no perturbations in climate statistics (i.e. whereby all scenarios have current climate statistics) to understand the variability inherent in the methodology. The results are indicative of the uncertainty that is a consequence of assuming a particular set of rainfall loss values for all 5% AEP events in a catchment under stationary climatic conditions.

4. Results

The two flood properties of most interest to practicing engineers and hydrologists are often flood volume (for applications such as detention basin design) and peak flow (for applications such as bridge/culvert design). We focus on these two model outputs when interpreting the results of this assessment.

4.1. Baseline WBNM model assessment

Some variability in event-based model performance is expected when simulating different floods with the same loss values. This is because different storms will have different intensities, durations and antecedent conditions. To understand the extent of underlying variability between the WBNM and GR4J results under current climate conditions, the methodology was applied to 256 sets of 100 sequences generated with unperturbed climatic statistics. The losses in WBNM were calibrated based on one set of 100 5% AEP events under current climatic conditions (as described in Section 3.1.2), giving an initial loss of 62.4 mm and a continuing loss of 2.47 mm/h. These losses were applied in all WBNM simulations. The results give an indication of the variability in WBNM model performance (relative to the GR4J results) due to natural climate variability as opposed to systematic climate change (Fig. 5).

It is clear that the event-based model performance is quite variable when a single set of loss parameters is used to simulate different events. For example, the average ratio of WBNM modelled flood volume to the GR4J flood volume (for a set of 100 sequences, represented by a single gridbox on the response surface) varies from 0.72 to 1.24 (Fig. 5a). While the flood volumes are modelled with relatively little bias on average (Fig. 5a), the median flood volumes are generally smaller for WBNM

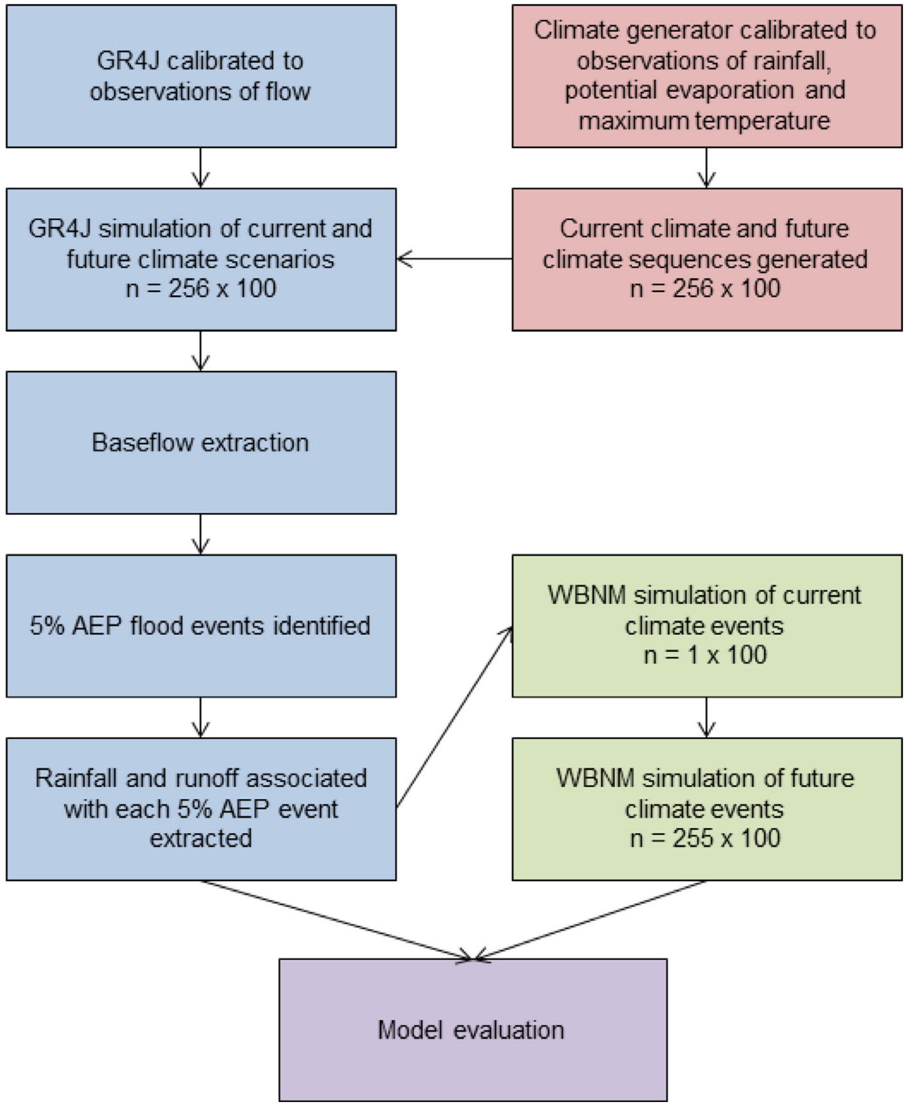

Fig. 4. Methodology for bottom-up climate change assessment. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

(Fig. 5b). This indicates that there is an asymmetric spread in the performance of the models for each scenario. The volume is significantly overestimated (relatively) for a small number of events, which results in an average ratio higher than the median.

A similar pattern is observed for peak flow (with median ratios smaller than average ratios). However, there is a tendency for WBNM to give larger peaks (relatively), with the average ratio of WBNM peak flow to GR4J peak flow being greater than 1.2 for all scenarios (Fig. 5c). The median ratios are generally close to one (Fig. 5d).

The tendency towards median results that are lower than the average results is attributed to differences in model structure. Because WBNM accounts for nonlinearity in catchment response (while GR4J is linear), the larger individual rainfall events are likely to produce proportionately greater flows than simulated in GR4J. These events will substantially increase the average WBNM to GR4J ratios, but have less influence on the median. Because the WBNM model losses were calibrated by minimizing KGE, which is strongly influenced by storm volume, the ratios for storm volume are centered approximately around one. The peak flow values tend to be larger in WBNM than GR4J due to the catchment linearity assumption in GR4J.

Overall, there is a reasonably high degree of variability in the outcomes of all four performance measures (Fig. 5). There is thus considerable potential for error associated with applying one set of losses to model different floods in a catchment even in a stationary climate. Some flows were substantially larger in WBNM than GR4J, while in other cases effective rainfall was zero with no runoff simulated. These results provide an estimate of the reference variability which will also be expected to occur in the climate change simulations.

4.2. Bottom-up climate change assessment of WBNM performance

In order to examine the WBNM model performance under climate change, the parameters wet season wet day persistence and β were perturbed from 0% to 30% (below and above the baseline values respectively) in 2% increments, giving a total of 256 different climate scenarios (including current climate). For each climate scenario, the WBNM model performance was assessed by calculating the average ratio of WBNM flow volume to GR4J flow volume (Fig. 6a); the median ratio of WBNM flow volume to GR4J flow volume (Fig. 6b); the average ratio of WBNM peak flow to GR4J peak flow (Fig. 6c); the median ratio of WBNM peak flow to GR4J peak flow (Fig. 6d). There are clear deviations in the WBNM results from the GR4J results under changing climatic conditions, beyond the previously discussed underlying variability (Fig. 5).

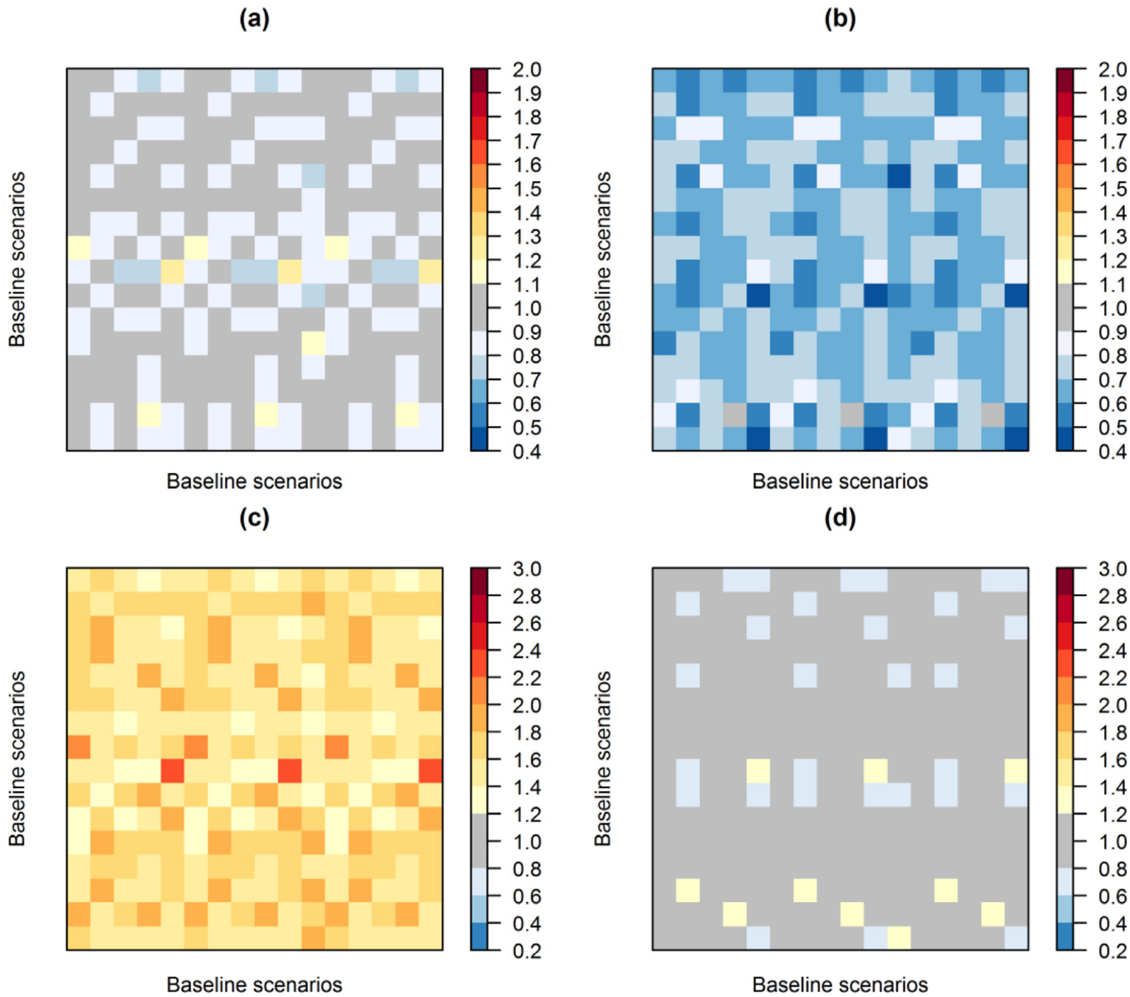

Fig. 5. Results of repeated assessment with unperturbed (current climate) statistics to understand uncertainty in workflow. The results are (a) average ratio of WBNM to GR4J flow volume (b) median ratio of WBNM to GR4J flow volume (c) average ratio of WBNM to GR4J peak flow (d) median ratio of WBNM to GR4J peak flow. (For interpretation of the colour scale in this figure, the reader is referred to the web version of this article.)

Decreasing the wet season wet day persistence means that the catchment will be drier on average prior to flood events. It follows that the rainfall losses calibrated to the (wetter) current climate scenario are likely to be too small, which could lead to the model overestimating the flood volume. This is reflected in the average performance results, which tend towards larger flood magnitude in WBNM than GR4J. However, for both peak and volume simulation, the wet season dryness has less effect on the median model performance (for which there is no discernible change). Decreasing the wet season wet day persistence thus leads to substantially larger estimates of flooding in WBNM for some of the floods, but has minimal effect on others. This highlights the uncertainty facing practicing engineers around how future climatic changes should be accounted for in event-based modelling.

The results for the 16 scenarios representing incrementally increasing wet season dryness (with no changes to the β parameter) are shown in Fig. 7. The boxplots show the ratios of modelled volume and peak between WBNM and GR4J results (a value close to one indicates good agreement). It is clear that the spread of results for the 100 storms simulated for each scenario is increasing, indicating that the variance in model performance is greater in the drier scenarios.

In some cases, particular event magnitudes are much larger in WBNM (with modelled volumes, for example, more than tenfold higher than the GR4J volumes). This is associated with very dry antecedent conditions prior to specific events. For example, one event identified from the scenario with a 30% decrease in wet season wet day persistence was the result of a total rainfall depth of 250 mm. The preceding weeks were almost entirely dry and the GR4J results gave only 14 mm runoff. The WBNM model, on the other hand, modelled 139 mm runoff. This highlights the substantial impact that antecedent conditions can have on model results in extreme cases.

There is more variability in the simulated antecedent conditions for scenarios with smaller wet season wet day persistence. The results show that the soil moisture modelled in GR4J on the day preceding each peak rainfall event became more variable with decreasing wet season wet day persistence. The standard deviation of the soil moisture store prior to the rainfall peak shows a clear relationship with the standard deviation of the model performance statistics, which indicates that the increased variability in event-based model performance is a consequence of the changing antecedent conditions (Fig. 8).

Because the model performance divergence was driven by increased variability in antecedent conditions, there is evidence that the continuous model (which can account for this) is able to better represent the drier scenarios. It follows that the continuous model results can be used as a benchmark for investigating appropriate loss values under drier conditions in the event-based model. The initial loss parameter in WBNM was recalibrated for three drier climate scenarios (10%, 20% and 30% decrease in wet season wet day persistence) to test for a systematic change in the calibrated value. We found that the optimal initial loss did

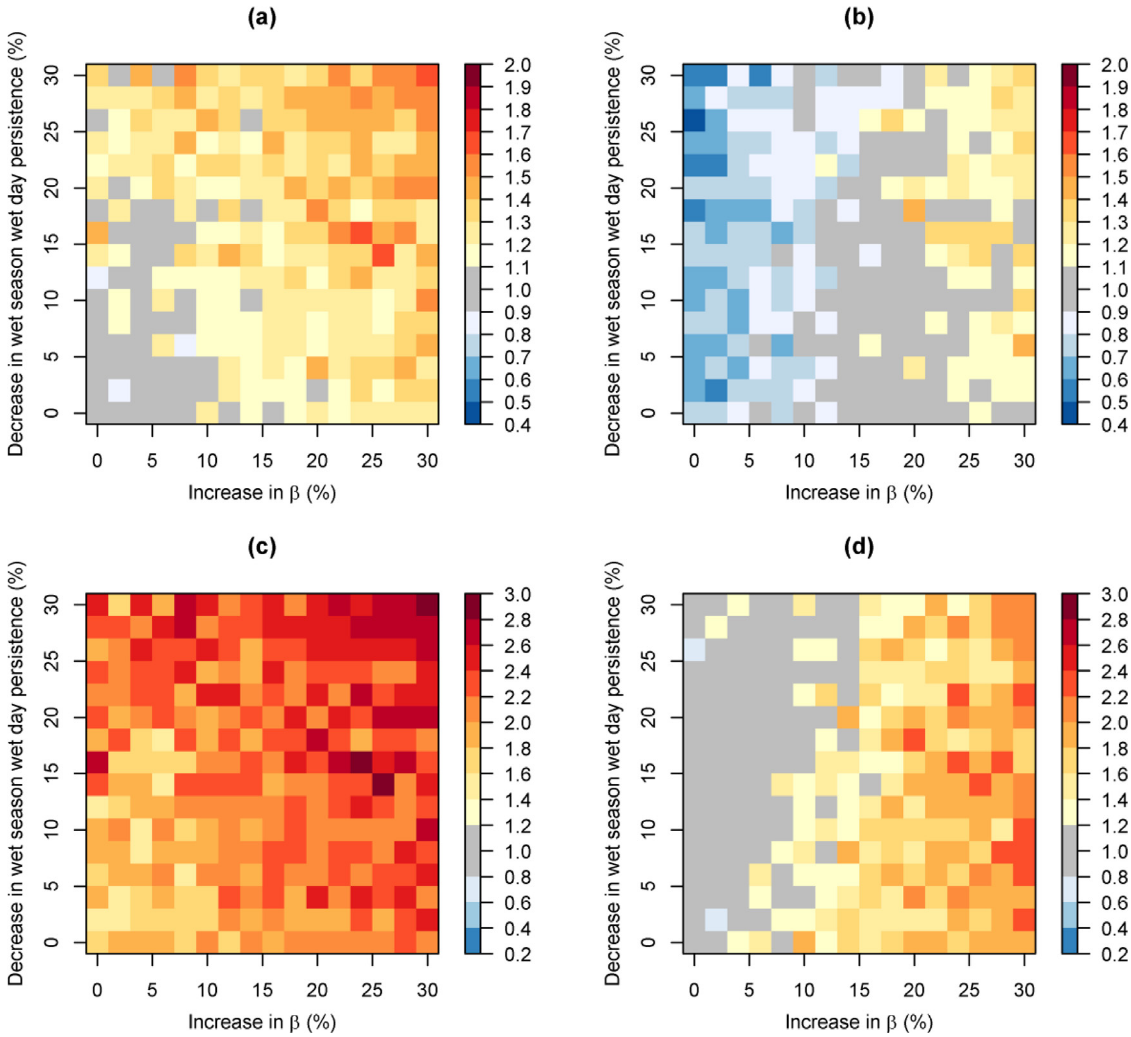

Fig. 6. Results of assessment with climatic statistics perturbed based on possible future climate projections for Southern Australia. The results are (a) average ratio of WBNM to GR4J flow volume (b) median ratio of WBNM to GR4J flow volume (c) average ratio of WBNM to GR4J peak flow (d) median ratio of WBNM to GR4J peak flow. (For interpretation of the colour scale in this figure, the reader is referred to the web version of this article.)

Table 1
Results of WBNM recalibration under drier future conditions, using GR4J results as a benchmark.

Scenario	Calibrated initial loss (mm)	Continuing loss (mm/h)	Average KGE over 100 modelled events
Current climate	62.4	2.47	−0.09
10% decrease in wet season wet day persistence	65.8	2.47	−0.31
20% decrease in wet season wet day persistence	67.2	2.47	−0.65
30% decrease in wet season wet day persistence	62.5	2.47	−0.89

not increase consistently with climatic dryness, but the optimized model performance degraded substantially for each increasingly dry scenario (Table 1). This indicates that the model results under future conditions cannot be improved by simply increasing the initial loss to account for drier antecedent conditions.

Considering now the β parameter of the gamma distribution for the daily rainfall, the general shift was towards wetter conditions as this parameter was increased (Figs. 2 and 3). The total rainfall leading up to the modelled events (averaged over 100 events per scenario) therefore also increased (Fig. 9), along with increases in the magnitude of 5% AEP rainfall events. However, as β was increased, consistently higher average and median ratios were found between the WBNM and GR4J peak flows and volumes (Fig. 6). This was contrary to our expectations. It was assumed that the calibrated losses would be too high for the wetter scenarios and the flood magnitude would then be smaller in WBNM relative to the GR4J results. This indicates that the deviation of the WBNM results from the GR4J results is not caused by changing antecedent conditions.

Based on these results, representation of rainfall losses was clearly less important than other model structural differences. The significance of this finding is that changing antecedent conditions will not always be the key source of future uncertainty in flood modelling; therefore, the common assumption that adopting continuous simulation will necessarily offer an advantage is not supported.

One plausible explanation for this result is that WBNM accounts for nonlinearity in the catchment response (Eq. (3)), whilst GR4J is a linear catchment model. This means that increases in 5% AEP rainfall depths will tend to lead to proportionately higher runoff in WBNM than

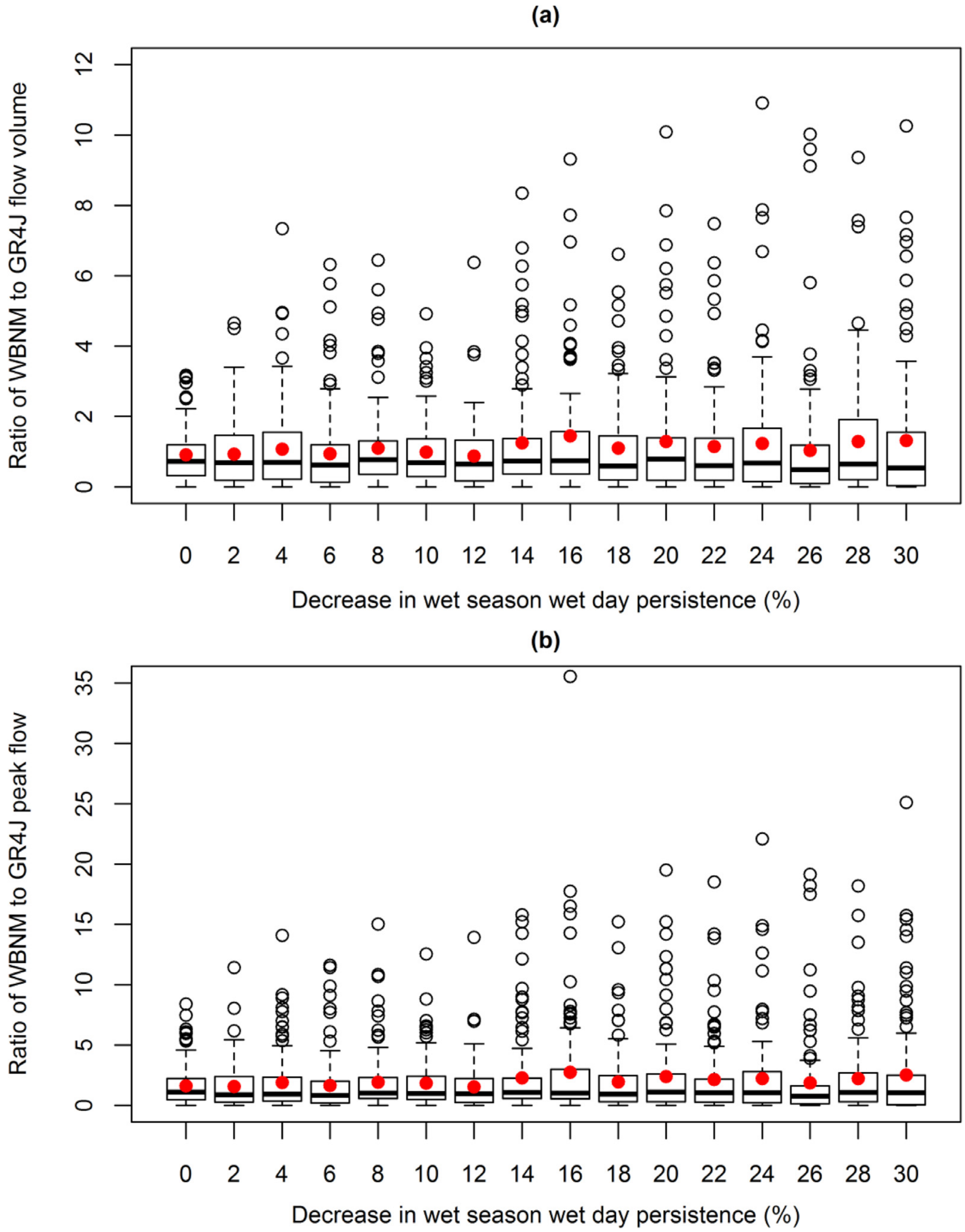

Fig. 7. (a) Flood volume and (b) flood peak ratios for the 100 5% AEP events modelled for each climate scenario with decreasing wet day persistence applied from June to November. The β parameter is not perturbed in these scenarios. The red points show the average model performance. It is clear that the overall spread of model performance results increases with decreasing wet season wet day persistence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

in GR4J. To check this hypothesis, the bottom-up climate change assessment was repeated assuming a linear catchment response in WBNM ($m = 1$, Eq. (3)). The peak flow results showed negligible divergence along the x-axis (Fig. 10), which indicates that representation of non-linearity in catchment response is the key cause of divergence between GR4J and WBNM in modelling future flood peaks. The storm volume statistics still diverged as rainfall intensity increased, particularly the median volume ratio (Fig. 10b).

Given that the volume ratios tend to increase as β increased, a greater proportion of the additional rainfall is being lost (i.e. not contributing to storm runoff) in GR4J. To understand the reasons for this, the rainfall 'sinks' in the two models were analyzed. WBNM simply subtracts any additional rainfall up until initial/continuing loss values are satisfied for the timestep, with the remainder being converted to additional runoff. For each scenario with increasing β, the average event rainfall was compared with the average effective rainfall in WBNM (linear, $m = 1$) to understand how much was absorbed through additional losses. In the current climate case the average rainfall depth absorbed by losses was 131 mm over the (100) 5% AEP events. This increased as β (and hence overall rainfall depth) increased, up to 151 mm for a 30% increase in β. Therefore, for the most intense extreme rainfall scenario, 20 mm additional rainfall was lost on average.

As GR4J has a more complex model structure, there are more potential mechanisms for the additional water to be lost. Firstly, some of

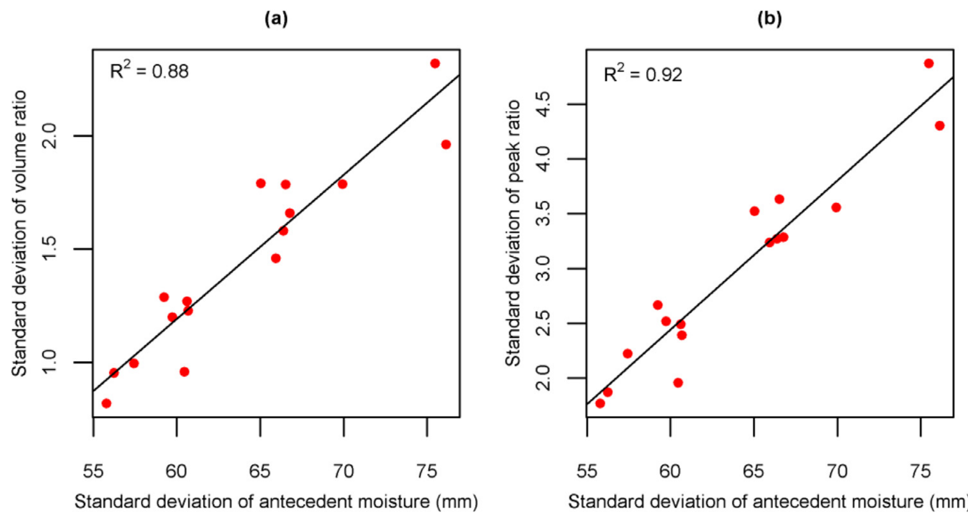

Fig. 8. Relationship between variability in antecedent condidtions and variability in model performance in replicating (a) volume and (b) peak flow. The antecedent conditions are indicated by the soil moisture store modelled on the day preceding the peak rainfall event associated with each 5% AEP flood.

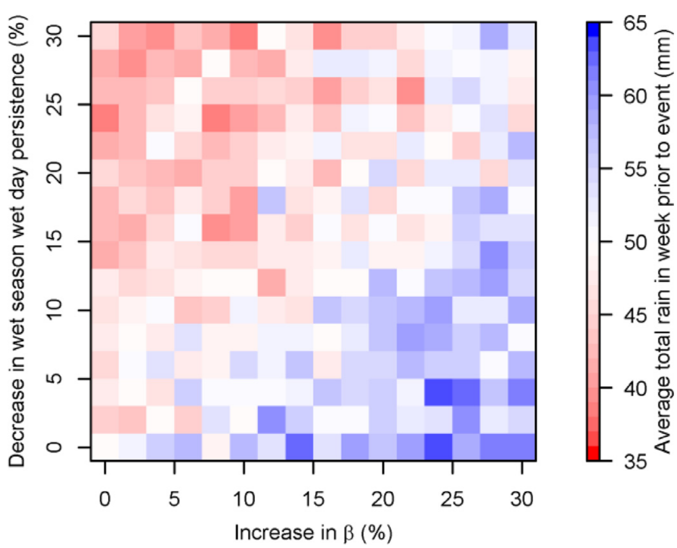

Fig. 9. Average of total rainfall in the week leading up to the 5% AEP rainfall event (100 in total) for each modelled scenario (256 in total). There is a general shift towards wetter conditions on average as the β parameter is increased, with a shift towards drier conditions on average as the wet season wet day persistance is decreased. (For interpretation of the colour scale in this figure, the reader is referred to the web version of this article.)

the additional rainfall is stored as additional soil moisture according to Eq. (3) in Perrin et al. (2003):

$$P_s = \frac{x_1\left(1-\left(\frac{s}{x_1}\right)^2\right)\tanh\frac{P_n}{x_1}}{1+\frac{s}{x_1}\tanh\left(\frac{P_n}{x_1}\right)}$$

where P_n is the total rainfall (mm), P_s is rainfall entering the soil store (mm), x_1 is the soil store capacity (calibrated to 1153 mm in this model) and s is the depth in the soil store (mm). For each scenario with increasing β and no change in wet season wet day persistence, the average total P_s over the (100) 5% AEP events was calculated. It was found that average P_s increased by 10 mm for a 30% increase in β. Secondly, GR4J considers transport of groundwater between catchments as a function of the level in the routing store according to Equation 18 in Perrin et al. (2003):

$$F = x_2\left(\frac{R}{x_3}\right)^{\frac{7}{2}}$$

where F is the groundwater exchange term (mm), R is the level in the routing store (mm), x_2 is the water exchange coefficient (mm) and x_3 is the reference capacity of the routing store. The depth of rainfall lost through groundwater exchange increased by 8 mm on average between the current climate simulations and those with 30% increase in β. Thirdly, the amount separated from the flow series through the baseflow filter increased by 12 mm on average.

In total, 30 mm additional rainfall was lost on average from GR4J for the scenario with β increased 30%, while the WBNM simulations lost only 20 mm of additional rainfall on average. This explains why the modelled volumes in WBNM tended to be proportionately higher than those in GR4J. In summary, the results demonstrate that relatively complex effects of model structure can become important when simulating floods under change, and it may be necessary to undertake specific testing of different model structures at a study site to understand how they will perform under change.

The results for the 16 scenarios with incremental increases in the β parameter with no change in wet season wet day persistence are shown in Fig. 11. Unlike the scenarios where wet season wet day persistence was perturbed, the variance in model performance shows no clear trend. This indicates that the variability in antecedent conditions was not strongly impacted by increasing the rainfall distribution, although antecedent conditions became wetter on average. Therefore, employing a continuous model that can dynamically account for antecedent conditions may not offer additional benefit (beyond the advantage already offered under current climate conditions) in reducing model uncertainty under future climate scenarios with increased rainfall distribution. Both the median and average ratios for flow and volume tend to increase as β increases, as indicated in Fig. 6.

5. Discussion

This study investigated divergence in event-based model performance relative to continuous model performance under climate change due to alterations in catchment antecedent conditions. The results demonstrated that drier climatic conditions led to increased variability in the performance of an event-based model relative to continuous model outputs (Fig. 7). This increased variability in performance was shown to correlate with increased variability in simulated antecedent

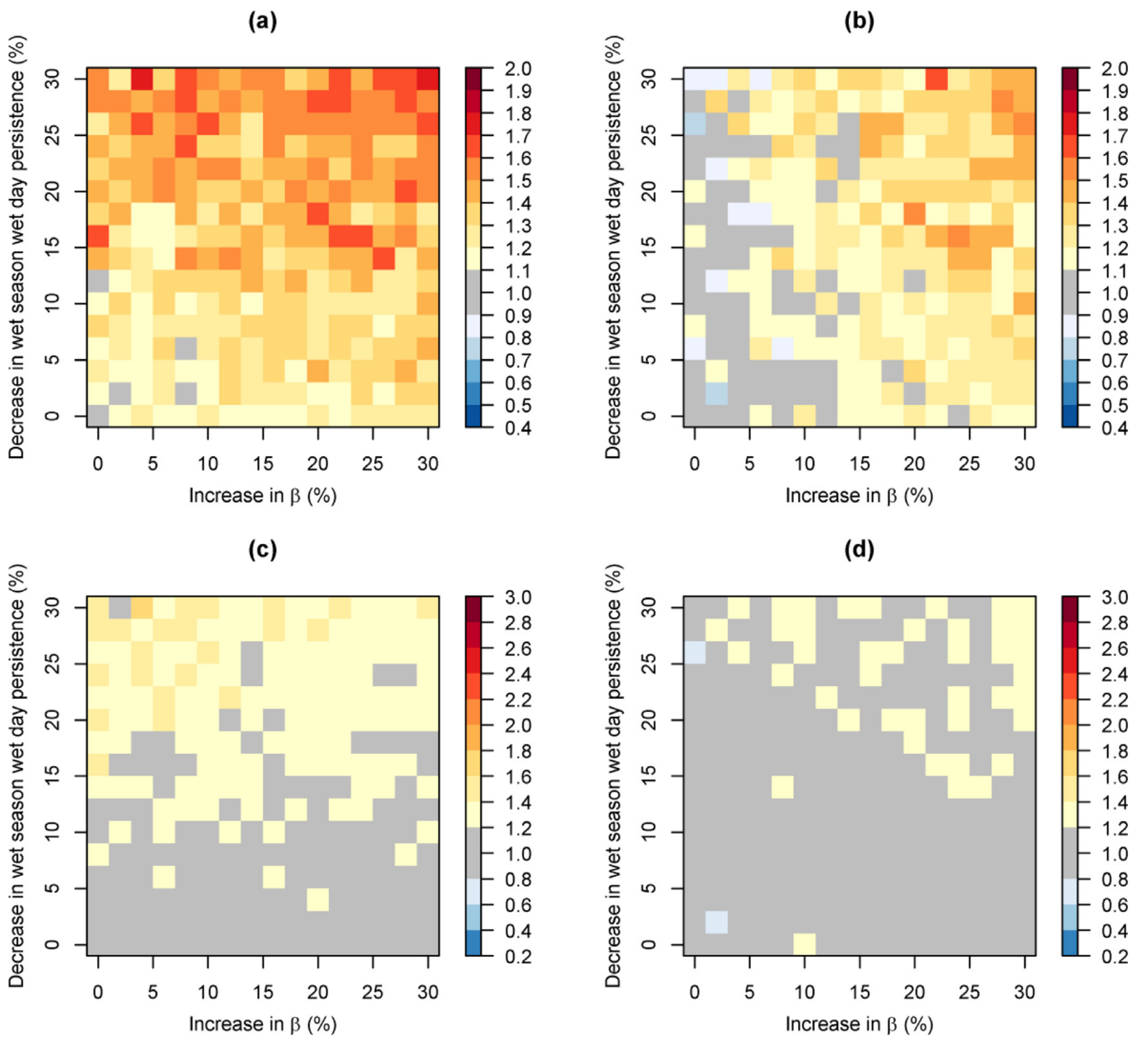

Fig. 10. Results of the bottom up climate change assessment repeated with linear catchment response in WBNM. The results are (a) average ratio of WBNM to GR4J flow volume (b) median ratio of WBNM to GR4J flow volume (c) average ratio of WBNM to GR4J peak flow (d) median ratio of WBNM to GR4J peak flow. Note that the current climate results [0,0] do not show the same tendency towards lower volumes and larger peaks in WBNM (as in Fig. 6), so the baseline for comparison is quite different. Therefore, when comparing these figures, the change in ratios over each response surface rather than the absolute values should be considered. (For interpretation of the colour scale in this figure, the reader is referred to the web version of this article.)

conditions (Fig. 8). The magnitude of performance divergence surpassed underlying variability and tended to increase for increasingly severe climatic change (Fig. 6). This suggests that continuous simulation could offer an advantage under drier future scenarios, but given that increases in extreme rainfall are also predicted for Australia, this is not sufficient to recommend a complete move away from event-based modelling.

Practicing hydrologists hoping to account for drier antecedent conditions in event-based models may be interested in whether systematic changes in the ideal loss parameters could be identified. The WBNM model was recalibrated against the GR4J results under increasingly dry climate conditions to investigate this. However, it was found that, even if the loss values were recalibrated, the event-based model could not perform as well under drier conditions. There was no consistent change in the calibrated initial loss value. This indicates that the parameterization of event-based models by adjusting design losses for climate change scenarios is not likely to be intuitive and region-specific testing may be required based on local projections. It is not recommended that initial loss values be increased under drier future conditions unless there is specific evidence to support this decision at the study site.

Adjusting the rainfall distribution to represent greater rainfall depths was not found to alter variability in the performance of the event-based model relative to the continuous model results (Fig. 11). The performance measures were impacted substantially (Fig. 6), but this was not consistent with (and therefore not dominated by) changing antecedent conditions. Rather, other differences in model structure were found to be more important when extreme rainfall was increased.

Because the continuous model assumes linearity in catchment response but the event-based model accounts for nonlinearity, the same increase in rainfall tended to give a greater increase in peak flow in the event-based model. The effect on the performance measures was more significant than that of changing antecedent conditions, which would be expected to lead to smaller peak flow values in the event-based model. It is unclear whether the assumptions around catchment nonlinearity in either model are optimal for simulating future floods (since the degree of nonlinearity is uncertain and varies between catchments). However, it is widely recognized that catchments do exhibit some nonlinearity, so the inflexible assumption of linear catchment response is a clear weakness in GR4J for simulation under changing conditions. It is possible that catchment nonlinearity could change in the future, since hydrologic changes can impact catchment geomorphology (Nanson et al., 1995; Lotsari et al., 2015). If the degree of nonlinearity in a given catchment's response is sensitive to changes in climate, models that allow the user to define a nonlinearity parameter (such as WBNM) may offer advantages over those in which catchment nonlinearity is fixed

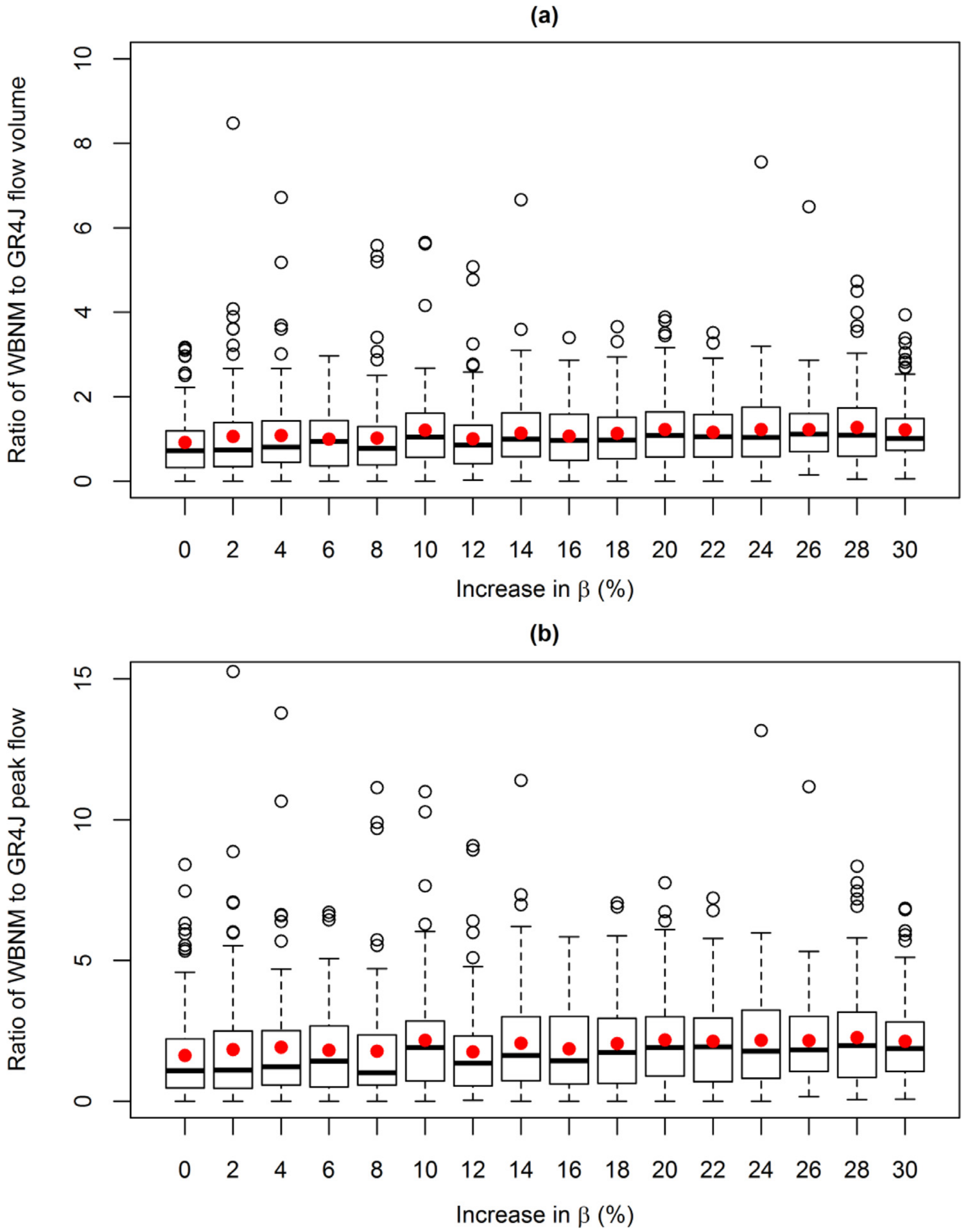

Fig. 11. (a) Flood volume and (b) flood peak ratios for the 100 5% AEP events modelled for each climate scenario with increasing β parameter, which shifts the rainfall distribution to favour higher intensities. The wet season wet day persistance is not perturbed in these scenarios. The red points show the average model performance. Both average and median model errors tend to increase with increasing β. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(as in GR4J) or implicit (as in SWMM). Investigating future changes in catchment nonlinearity is outside the scope of this study, since it would require detailed hydraulic modelling and testing of many scenarios, but this would be an interesting topic for future research.

Performance divergence in simulated flood volumes was found to relate to differences in how rainfall is lost (i.e. not converted to runoff) in the models. In WBNM, increased continuing losses meant that the total modelled losses were larger under the increased extreme rainfall scenarios. In GR4J, there are three mechanisms that increase total rainfall lost: (1) more rainfall lost to the soil moisture store; (2) more water removed through the baseflow transfer function and (3) more flow separated from the model outputs as baseflow. In combination, these three mechanisms gave a relatively larger impact on storm volume in GR4J than the additional continuing losses in WBNM, meaning that the GR4J flood volumes were smaller overall. While GR4J has a more complex structure, it is not clear that this offers a more realistic representation. Therefore, it is not possible to say which model might simulate future storm volumes more accurately when extreme rainfall is increased.

The findings of this study contrast with previous work that recommends the use of continuous simulation for climate change scenarios in order to account for changing antecedent conditions (Johnson et al., 2016); we find that future model performance may be more dependent on other modelling assumptions in some cases. Therefore, practicing hydrologists should carefully consider the specific projections for the study area along with model structural features when selecting a flood model for climate change assessment. The common assumption that continuous simulation will necessarily offer an advantage under changing conditions is not supported. For cases where drier average conditions and increased extreme rainfall are projected, this analysis suggests continu-

ous models that account for catchment nonlinearity may improve future flood prediction.

It is worth noting that other catchment variables besides extreme rainfall intensity and antecedent conditions are also expected to be affected by climate change. These include changes in vegetation due to alterations in temperature, carbon dioxide concentrations and rainfall, as well as changes in plant water use efficiency due to increased carbon dioxide concentrations (Liu et al., 2016; Li and Ishidaira, 2012). As mentioned above, catchment geomorphology could also be impacted by changing hydrologic regimes. Processes like these are not simulated in common event-based or continuous hydrologic models. Therefore, both event-based and continuous model performance may be subject to parameter nonstationarity that is not captured in the comparisons here. The impact of these environmental changes on continuous model performance in particular has been the subject of several previous studies (Westra et al., 2014; Vaze et al., 2010; Merz et al., 2011; Coron et al., 2014; Coron et al., 2012; Brigode et al., 2013; Thirel et al., 2015; Fowler et al., 2016). This study was able to compare model performance under change and deduce key potential sources of relative error, but does not aim to prove that either model is able to provide an optimal representation of future flow. To better understand how catchment response could be affected by future ecological changes, it may be useful to test climate change scenarios in more complex ecohydrologic models that are able to simulate vegetation dynamically. Ultimately, all models are subject to some limitations in their representation of catchment dynamics, so it will also be important to utilize available observations of catchments under change to improve process understanding going forward.

Based on the results of this study, practitioners using event-based models to simulate future flows should consider two sources of uncertainty relating to losses. Firstly, there is uncertainty inherent in the assumption that losses calibrated to past events will apply to a separate future event under consistent climatic conditions (demonstrated by the variability in results shown in Fig. 5). Applying the calibrated losses gave zero flow for some current climate events and very large flows (compared to the continuous model results) for others. This uncertainty is well recognized in the hydrology community (Tramblay et al., 2010; Berthet et al., 2009; Pathiraja et al., 2012) and can be incorporated in modelling studies by applying ensembles of possible loss values constrained by a probability distribution (Loveridge and Rahman, 2014) to understand runoff sensitivity.

Secondly, there is uncertainty associated with future hydrologic changes that could impact antecedent conditions and typical catchment response (Fig. 6). This is generally not considered in flood modelling and design, but we find that applying future climate scenarios substantially increases model uncertainty and alters the relative performance of different types of models (Fig. 6). Here we have demonstrated the issue using a deterministic initial/continuing loss approach, but the same principle would likely apply to ensembles that are constrained based on past observations. This would be a useful area of future research.

The effect of climate change on an event-based model that uses initial/continuing losses, as per standard industry practice in Australia (Ball et al., 2016), has been tested here. The results for drier climatic scenarios are likely to be analogous for any model in which losses are parameterized based on knowledge of past catchment behavior, including SWMM and ReFH (Kjeldsen, 2007). However, the equations translating excess rainfall to runoff differ. This work has shown that assumptions around the representation of the catchment response could change the sensitivity of these models to scaling rainfall to account for climate change. Because ReFH assumes linear catchment response and SWMM (which applies the Manning relationship) implicitly assumes a higher rate of nonlinearity than the default in WBNM, it is likely that, for equivalent climatic changes, ReFH would lead to smaller increases in flood risk than WBNM, with SWMM leading to the largest increases in flood risk. The implications of structural differences in common event-based models for studies that involve rainfall scaling without recalibration should be investigated through further research.

6. Conclusion

Projected future changes in climate have been shown to impact the relative performance of event-based and continuous hydrologic models in simulating flooding. Drier climatic conditions and increased rainfall distribution were simulated based on GCM projections for Southern Australia.

For the drier climate scenarios, there was a tendency for the event-based model to give increasingly greater estimates of future flood magnitude for some individual events. This occurred because drier antecedent conditions meant that the losses calibrated to the current climate were too small. However, because the antecedent conditions prior to one particular flood event will not necessarily change when the overall climate becomes drier, the results were not affected in every case. Increasing variability in antecedent conditions under drier future scenarios was shown to correlate with variability in event-based model performance. This indicates that the uncertainty in event-based model results increases when attempting to simulate a drier future climate and supports the notion of using continuous simulation to dynamically account for catchment moisture.

When the rainfall distribution was perturbed to favor greater rainfall intensities, the event-based model also showed a tendency to simulate larger floods than the continuous model. In this case, the results were more consistent between different individual events and variability in performance did not increase. The changes were not consistent with the alterations in antecedent conditions (which would lead one to expect smaller floods in the event-based model) and were instead attributed to differences in model structure. Because the event-based model accounts for nonlinearity in catchment response, but the continuous model is linear, increased rainfall tended to translate to greater peak flow increases in the event-based model. Representation of moisture storage in the catchment also contributed to performance divergence for flood volume. This is in contrast with the assumption that changing antecedent conditions represents the key source of uncertainty in event-based modelling of future floods.

Based on this assessment, engineers and hydrologists should be aware of the potential for event-based model performance changes in a changing climate. In some cases, the variability in model performance may be impacted by alterations in antecedent conditions (as in the case of the drier climate scenarios tested here). However, other assumptions inherent in the model structure will sometimes be more important. Overall, the results of this study do not support a blanket shift towards the use of continuous simulation for future flood assessments. In a changing climate, it is especially important that hydrologists continue to improve physical process representation in flood models.

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